APPLICATION OF INVERSE THEORY IN OPEN PIT BLASTING

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENT FOR THE DEGREE OF

Bachelor of Technology

In

Mining Engineering

By

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DEPARTMENT OF MINING ENGINEERING

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CERTIFICATE

This is to certify that the thesis entitled **"Application of Inverse Theory in Open Pit Blasting"** submitted by Sri Santanu Kumar Barik (Roll No. 109MN0102) in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Mining Engineering at the National institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in this thesis has not formed the basis for the award of any Degree or Diploma or similar title of any university or institution.

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CONTENTS

ABSTRACT

Blasting is a crucial part in mining operation. Proper blasting practice not only reduces the adverse effects like peak particle velocity but also improve the production and productivity. The blasting in open pit mine is controlled by number of parameters like spacing, burden, quantity of explosive etc. The production and productivity are measured by power factor, throw, and drop.

Numerous models have been developed to calculate the powder factor, drop, and throw using spacing, burden, hole depth and explosive charges etc. as input variables, which means that for known input variables, powder factor, throw, and drop can be calculated. However, field mining engineers are more interested about what should be the suitable values of input parameters to get a specific factor, throw, and drop. In most cases this has been done on a trial and error basis to fix the values of input parameters.

A technique was developed to predict a nearly optimum set of blast design parameters from the nine variable design parameters (drill penetration rate, bench height, burden, spacing, hole depth, sub-grade drilling, stemming, blast round, and length to width ratio) that largely affect the shape (throw and drop) and the PF values of blasted muck piles. A stepwise forward multivariate regression algorithm was applied to generate optimum forward equation for powder factor, drop, and throw parameters. A linear inverse theory was applied to develop linear equations for independent variables. The developed method was applied in a limestone case study mine and results revealed that the this approach could be a good methods for selection of blasting parameters to get desire outputs.

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CHAPTER 1

INTRODUCTION

OBJECTIVE

1.INTRODUCTION

The main objective of fragmentation by blasting is to achieve the optimum powder factor, which may be defined as the powder factor required for the optimum fragmentation, throw, ground vibration, etc. for a specified blast condition to minimize the overall mining cost. Presently, the powder factor is established through the trial blasts. However, powder factor may be approximated using rock, design and explosive parameters. The blast design parameters were varied in these blasts in an orderly fashion. The intention of this exercise was to produce a better shape to the blasted mucks by increasing the throw and drop characteristics so that the muck could be easily removed by the payloaders.

Open pit mining requires close attention to geology,geotechnical planning,scheduling of earthmoving equipment,drill and blast technology and safety.Constant monitoring and improvement,each aspect of open pit mining aims to control and reduce costs and improve the extraction of ore from the ground in the safest,most efficient manner (Hustrulid 1999).

Optimizing blasting and drilling in open pit mining is a difficult task which depends on the availability of current reliable data on rock susceptibility to explosion for accomplishing the dual task of choosing an optimal network of holes and specifying optimal specific distribution of explosive energy(Das 1993). The chief goal of any blasting technique for a mining project is to provide adequate fracturing of the rock mass to minimize the mine-to-mill costs while maintaining the technical, environmental and safety standards. Improper fragmentation wastes explosive energy and creates environmental problems such as ground vibrations, air blasts and fly rocks. The shape and the powder factor (PF) of blasted muck piles are important parameters that reveal the state of fragmentation vis-a-vis the efficacy of blast design parameters.

Moreover, proper blasting is crucial for mining engineers not only for improving the fragmentation of a blasted muck pile but also reducing the peak particle velocity (PPV). Numerous models have been developed to calculate the PPV and fragmentation size using spacing, burden, hole depth and explosive charges as input variables, which means that for known input variables, PPV and fragmentation size can be calculated. However, field mining engineers are more interested about what should be the suitable values of input parameters to get a specific PPV value and fragment size. The environmental laws of different countries have set different PPV values for mining operations occurring near residential areas. Therefore, mine operators are more interested in what should be suitable values of input parameters such that it will restrict the PPV within the limit and at the same time generate a better fragment size. In most cases this has been done on a trial and error basis to fix the values of input parameters.

This thesis focusing on developing an inverse theory-based model to optimize the input parameters for blast design such that it can improve the fragmentation size. The linear inverse theory is applied in a limestone deposit. Linear inverse theory has an advantage of providing the optimum solution; however, in this case study the solution is not feasible due to the singularity of the inverse matrix. An algorithm was applied which will change a singular matrix to a non-singular matrix with minimum modification of the matrix elements. This will help to solve any linear inverse problem.

OBJECTIVES

The main objectives of this thesis are

Validation of the linearity assumptions of all blasting parameters to generate forward equations for powder factor, drop, and throw

Development the optimum forward equations for powder factor, drop, and throw using stepwise forward regression models

Development of the linear inverse theory equation to calculate the optimum input parameters configuration for desire output value.

Case study of the proposed method in a limestone mine

CHAPTER 2

LITERATURE REVIEW

2.LITERATURE REVIEW

The term blastability is used to indicate the susceptibility of the rock mass to blasting and is closely related with the powder factor. Several approaches have been used for estimating the effects of blasting paramters. While some researchers tried to correlate it with the data available from laboratory and field testing of rock parameters, some others have related it with rock and blast design parameters, and yet some others have tried to estimate the blast dependent parameters through approaches based on the drilling rates and/or blast performances in the field. The latest improvements in computer methods have also opened up new vistas to the researchers to use various artificial intelligence algorithms.

Hino (1959) proposed that blastability (named as Blasting Coefficient(BC) by him) is the ratio of compressive strength (CS) to tensile strength (TS) of rockmass, Langefors (1978) proposed a factor to represent the influence of rock and defined it by C_0 when it refers to a limit charge (zero throw condition). C indicates the value of the factor including a technical margin for satisfactory breakage, and is given by $C=1.2 \times C_0$. For blast designs, C = 0.4 kg/m3 is considered directly and with the incorporation of desired tendency for breakage and throw based on geological and design parameters alteration in powder factor is required. This alteration factor may be regarded as geometric or fixation factor. Fraenkel (1954) proposed that "for practical use the blastability of rock, C (kg/m3), can be determined by test blasting with one single vertical hole with 33mm bottom diameter, hole depth 1.33m and with that charge which is needed to give a 1m high vertical bench and 1m burden a breakage and throw of maximum 1m". Fraenkel (1954) proposed the following empirical relationship between the height and diameter of the charge, hole depth, maximum burden and blastability. Hansen (1968) suggested the following equation to estimate the quantity of explosive required for optimum fragmentation at Marrow Point Dam and Power Plant Project. Heinen & Dimock (1976) They proposed a method for describing blastability of rockmass based on the field experience at a copper mine in Navada (USA). They relate the average powder factor with seismic propagation velocity in rockmass and found that powder factor increases with the increased rock propagation velocity Ashby (1977) developed an empirical relationship to describe the powder factor required for adequate blast (in Bougainville Copper Mine) based on the fracture frequency representing the density of fracturing and effective friction angle representing the strength of structured rockmass..

Praillet R. (1980) he determines the burden value as a function of Bench height, charge density,Detonation velocity,Stemming height,Compressive strength,Components that depends upon the loading equipment size.Fundamental research on blast design and to describe the rockmass viewing the blasting operation is going on. It is believed that it may be possible to get a universal methodology to determine the blastability, which will incorporate blast outcomes and be able to relate closely with the powder factor for different geo-mining condition. Biran (1994) observed that many empirical formulas have been used over 200 years for selection of proper charge size and other parameters for good fragmentation. Uttarwar and Mozumdar (1996) studied the blast casting technique that utilizes explosive energy to fragment the rock mass and cast a long portion of it directly into previously worked out pits. The technique depends on factors like bench height and helps in efficient trajectory of thrown rock and so in the height to width ratio. This technique is most effective with explosives that maximize ratio of heave energy to strain energy. Higher powder factor supports the technique. Optimal blast-hole diameter and inclination, stemming and decking method used, the burden to spacing ratio, delay intervals and initiation practices help in effective blasting. Bhandari (2004) developed a blast information management system (BIMS) where all the data in the mining operation are stored, analyzed, audited, documented and managed. These can be used to optimize the whole process. They observed that use of software for blasting operation i.e. BIMS makes the job simpler. It is easy to use, user friendly, data entry, reliable storage and analysis and can be customized easily. It saves time and cost to get the impact of a particular design. It helps to train and assess the effects of a certain drill and blast design for people and organizations that use blasting.

CHAPTER 3

METHODOLGY

INVERSE THEORY

PROPOSED THEORY

3.METHODOLOGY

3.1 Multivariate linear regression

Multivariate linear regression analysis method is a statistical technique for estimating the linear relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable with independent variables. Regression analysis helps one understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Rregression analysis estimates the conditional expectation of the dependent variable given the independent variables – that is the average value of the dependent variable when the independent variables are fixed.The focus is on a quantile, or other location parameter of the conditional distribution of the dependent variable given the independent variables. In all cases, the estimation target is a function of the independent variables called the regression function.

Regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. In circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables.

Multi-variate regression models involve the following variables:

a) The unknown parameters denoted as β, which is a vector.
b) The independent variables, X.
c) The dependent variable *Y*.

In various fields of application different terminologies are used in place of dependent and independent variables.

A regression model relates *Y* to a function of X and β.

$$Y \approx f(\mathbf{X}, \boldsymbol{\beta}) \qquad \text{(Eqn-1)}$$

To carry out regression analysis, the form of the function *f* must be specified. Sometimes the form of this function is based on knowledge about the relationship between *Y* and X that does not rely on the data. If no such knowledge is available, a flexible or convenient form for *f* is chosen.

Assume now that the vector of unknown parameters β is of length *k*. In order to perform a regression analysis the user must provide information about the dependent variable *Y*:

- In this thesis $N > k$ data points are observed. In this case, there is enough information in the data to estimate a unique value for β that best fits the data in some sense, and the regression model when applied to the data can be viewed as an overdetermined systems in β. Therefore the regression analysis provides the tools for:

Finding a solution for unknown parameters β that will, for example, minimize the distance between the measured and predicted values of the dependent variable *Y* (also known as method of least squares).

Under statistical assumptions, the regression analysis uses the surplus of information to provide statistical information about the unknown parameters β and predicted values of the dependent variable *Y*.

The purpose of regression analysis is to analyze relationships among variables. The analysis is carried out through the estimation of a relationship

$y = f(x1, x2, ..., xk)$ (Eqn-2)

and the results serve the following two purposes:

- Answer the question of how much y changes with changes in each of the x's (x1, x2,...,xk), and
- Forecast or predict the value of y based on the values of the X's

Under this estimation of parameters is done through a method called Method of least squares.

A Simple Regression Model can be written as

Value of Dependent variable = Constant +Slope×Value of Indep. variable + Error

$Y = A + \beta \times X + E$ (Eqn-3)

- Constant (A), Slope (β) and Error (E) are unknown.
- You observe N pair of values of dependent and independent variables.
- Regression analysis provides reasonable (statistically unbiased) values for slope(s) and intercept

The method is to estimate the parameters of the model**,** based on the observed pairs of values and applying a certain criterium function (the observed pairs of values are constituted by selected values of the auxiliary variable and by the corresponding observed values of the response variable), that is:

Observed values x_i and y_i for each pair i, where i=1,2,...,i,...n
Values to be estimated A and β and $(Y_1, Y_2, ..., Y_i, ..., Y_n)$ for the n observed pairs of values

Object function (or criterium function)

$$\Phi = \sum_{i=1}^{n} \left(y_i - Y_i\right)^2 \qquad \text{(Eqn-4)}$$

In the least squares method the estimators are the values of A and B which minimize the object function. Thus, one has to calculate the derivatives ∂Φ/∂A e ∂Φ/∂ β, equate them to zero and solve the system of equations in A and β.

3.2Inverse Theory:-

The process of predicting the numerical values of a set of model parameters of an assumed model based on the set of data or observations .

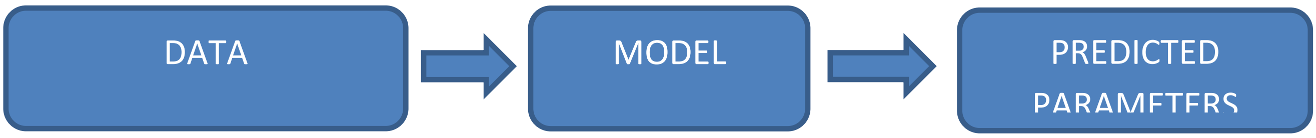

Figure 1:Flowchart for inverse theory

The model is the relationship between model parameters and the data,It may be linear or non linear.

Model Parameters:-

are the numerical quantities that one is attempting to estimate.The choice of model parameters is unusually problem dependent and quite often arbitrary.

Data are simply the observations or measurements one makes in an attempt to constrain the solution of some problem of interest.

It is important to realize, that there is much more to inverse theory than simply a set of estimated model parameters Unlike a mathematical inverse which either exists or doesn't exist there are many possible approximate inverses.These may give different answers part of the goal of an inverse analysis is to determine if the answer obtained is reasonable,valid.

Considering a discrete case example with two observation(N=2) and three model parameters (M=3)

$$D_1=2m_1 +0m_2-4m_3 \qquad \text{(Eqn-5)}$$

$$D_2=m_1+2m_2+3m_3 \qquad \text{(Eqn-6)}$$

Which may be written as:

$$\begin{bmatrix} D_1 \\ D_2 \end{bmatrix} = \begin{bmatrix} 2 & 0 & -4 \\ 1 & 2 & 3 \end{bmatrix} \begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix}$$

Or simply,

D=Gm

$$G=\begin{bmatrix} 2 & 0 & -4 \\ 1 & 2 & 3 \end{bmatrix}$$

In the case of a discrete linear inverse problem describing a linear system.Getting the forward problem set up in matrix notation is essential before it can be inverted.

The logical next step to take is.

D=Gm

And invert it for an estimate of model parameters(estimated)

$M^{estimated}=G^{inverse}d$

And $GG^{inverse}=I$,where I is the identity matrix

G^T denotes the matrix transpose of G. This equation simplifies to:

$$G^TGm = G^Td \qquad \text{(Eqn-7)}$$

After rearrangement, this becomes:

$$m = (G^TG)^{-1}G^Td \qquad \text{(Eqn-8)}$$

This expression is know as the Normal Equation and gives us a possible solution to the inverse problem.

The main goals of an Inverse Analysis:-

Estimates of a set of model parameters, Bounds on the range of acceptable model parameters, Estimates of the formal uncertainities in the model parameters., How sensitive is the solution to small changes in the data, Where and what kind of data are best suited to determine a set of model parameters, Is the fit between predicted and observed data adequate, Is a more complicated model significantly better than a more simple model

3.3 Proposed Theory:-

3.3.1 Forward Theory:-

The process of predicting data based on some physical or mathematical model with a given set of model parameters.

Schematically it can be presented as:

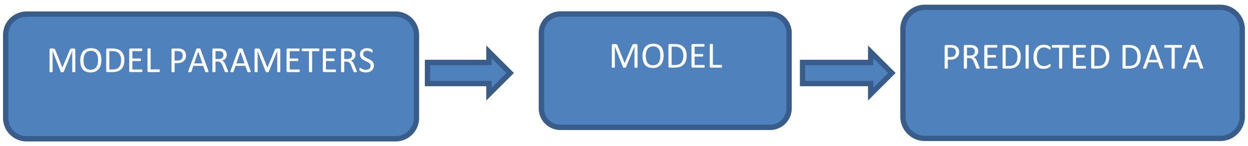

Figure 2:Flowchart for Forward theory

In statistics, linear regression is an approach to modeling the relationship between a scalar dependent variable y and one or more explanatory variables denoted X. For more than one explanatory variable, it is called multiple linear regression and this is distinguished from the multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

The blasting parameters are used all at a time, knowing the optimum value of such a parameter using the R^2 value so generated by the SPSS software, the maximum R^2 valued parameter is kept as selected variable and the next variable is inserted into the system. This cycle is continued till all the variables are optimized. This results in obtaining the proper optimization of all the blasting parameters. Thus a Regression modeling equation is developed.In order to validate the forward theory there are certain assumptions that should be taken care of or the forward theory cannot be applied.There are a total of 6 assumptions. When we choose to analyse the data using multiple regression, part of the process involves checking to make sure that the data to analyse can actually be analysed using multiple regression. We need to do this because it is only appropriate to use multiple regression if the data "passes" the following assumptions that are required for multiple regression to give a valid result.The 6 assumptions are:-

- The dependent variable should be measured on a continuous scale (i.e., it is either an interval or ratio variable).
- Two or more independent variables, which can be either continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable).
- Should have independence of observations
- There needs to be a linear relationship between (a) the dependent variable and each of your independent variables, and (b) the dependent variable and the independent variables collectively.
- The data needs to show homoscedasticity, which is where the variances along the line of best fit remain similar as you move along the line.
- The data must not show multicollinearity, which occurs when you have two or more independent variables that are highly correlated with each other

CHAPTER 4

CASE STUDY

4.CASE STUDY

The study was carried out on an limestone ore mine situated in some part of Philippines. Blast design data was obtained from a limestone quarryin the Philippines. The annual production of the limestone quarry is over 3 Mt. The quarry is worked in three sections, namely West, Central and East. This study pertains to data fromthe East and Central sections, where the limestone beds, separated at 2–3 m intervals, dip at an inclination of 30–40u. The geology of the deposit was quite difficult due to frequent shaly and clayey intrusions. The compressive strength of limestone was 40 MPa and the grade varied from 42.5 to 52.5%, the cutoff grade was 47% and the specific gravity of limestone was 2.4. The sections consisted of benches ranging 6–9 m in height. The loading operation was mainly performed by 5 m^3 payloaders (front end loaders). The blasted muck was loaded on 35 and 50 t rear dump trucks. The chief goal of any blasting technique for a mining project is to provide adequate fracturing of the rock mass to minimise the mine to mill cost while maintaining the technical,environmental and safety standards.Improper fragmentation wastes explosive energy and creates environmental problem such as ground vibrations,air blasts and fly rocks.The shape and the powder factor(PF) of blasted muck piles are important parameters that reveal the state of fragmentation via the efficiency of blast design parameters.In the present study,the shape of the muck pile pertains to the throw and drop characteristics of the muck pile.Throw describes the lateral spreading of the muck pile,while drop describes the maximum height of the blasted muck pile.The shape parameters affect the productivity of loading equipment. Burden B, spacing S, bench height H, stemming T, total explosive quantity of ANFO in a blast round Q and length to width (L/W) ratio of the blast round were the blast design parameters that were varied in the field scale blasts for improving desired outputs. The drill penetration rate PR was recorded during the entire drilling period in all the blast rounds, as it varied significantly for blast rounds at different locations, affecting the explosive quantity charged in the entire blast round.
According to the above study the parameters that affect or on which blasting depend ;-

a)Dependent Variables

b)Independent Variables

Basically Independent variables are the variables that are expected to affect the Dependent variables.In this case we have 7 independent variables and 3 dependent variables.

Independent Variables-

- Drill Penetration Rate (m/h),
- Bench Height (m),
- Burden (m),
- Spacing (m),
- Stemming (m),
- Blast Round (kg),
- Length to Width Ratio

Dependent Variables-

- Throw(m)

- Drop(m)
- PF(kg t^{-1})

CHAPETR 5

RESULTS
VALIDATION OF ASSUMPTIONS

FORWARD THEORY MODEL

INVERSE THEORY MODEL

5.RESULTS

The assumptions as discussed earlier are the necessary to give a valid result.So,its important to see whether the variables meet the requirements of the assumptions to provide a valid and reasonable result.

5.1 Validation of assumptions:-

When we choose to analyse the data using multiple regression, part of the process involves checking to make sure that the data to analyse can actually be analysed using multiple regression. We need to do this because it is only appropriate to use multiple regression if the data "passes" the following assumptions that are required for multiple regression to give you a valid result.

The continuous scale of the dependent variable can only be measured through the different Histograms of The three dependent variables.

Figure 3-5:present histograms of three dependent vaiables .From the histograms it is observed that throw parameters is following skewed distribution;whereas drop and poeder factors are following nearly Gaussian distribution.These distributions shape reveal that all three paramaters are continuous

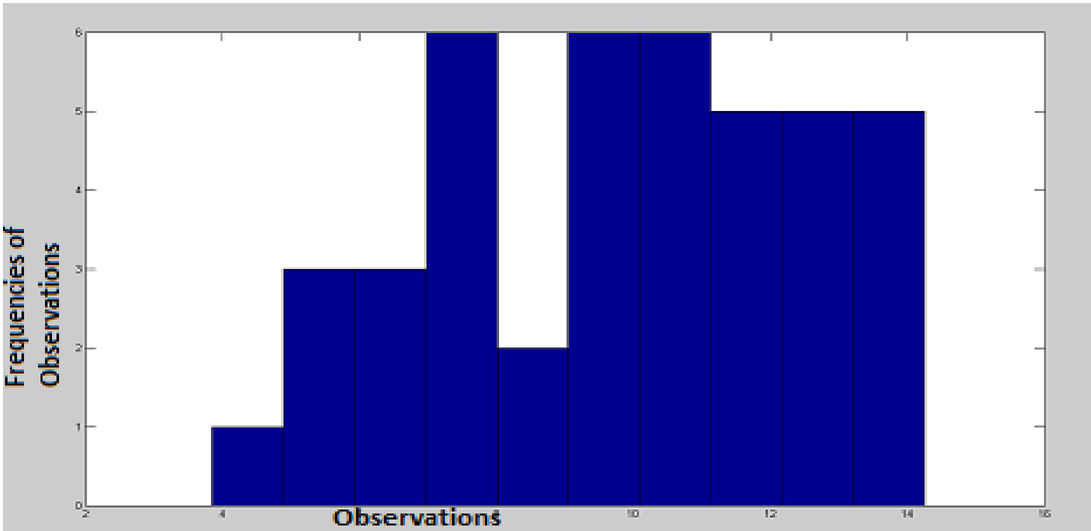

Fig 3.Histogram for Throw:

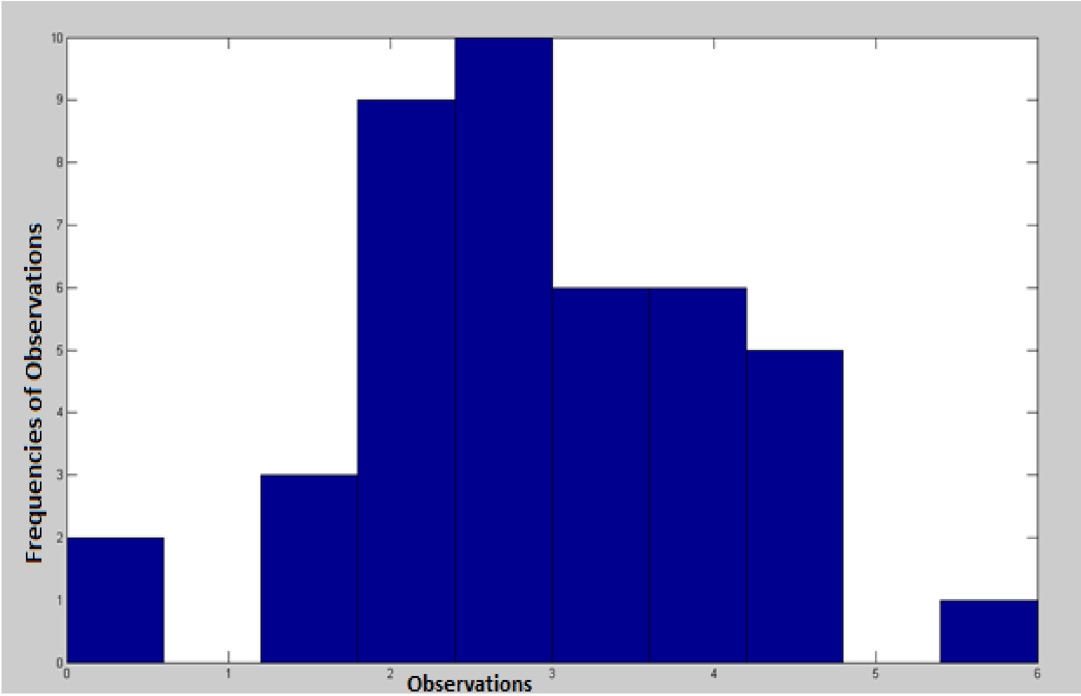

Fig 4.Histogram for Drop

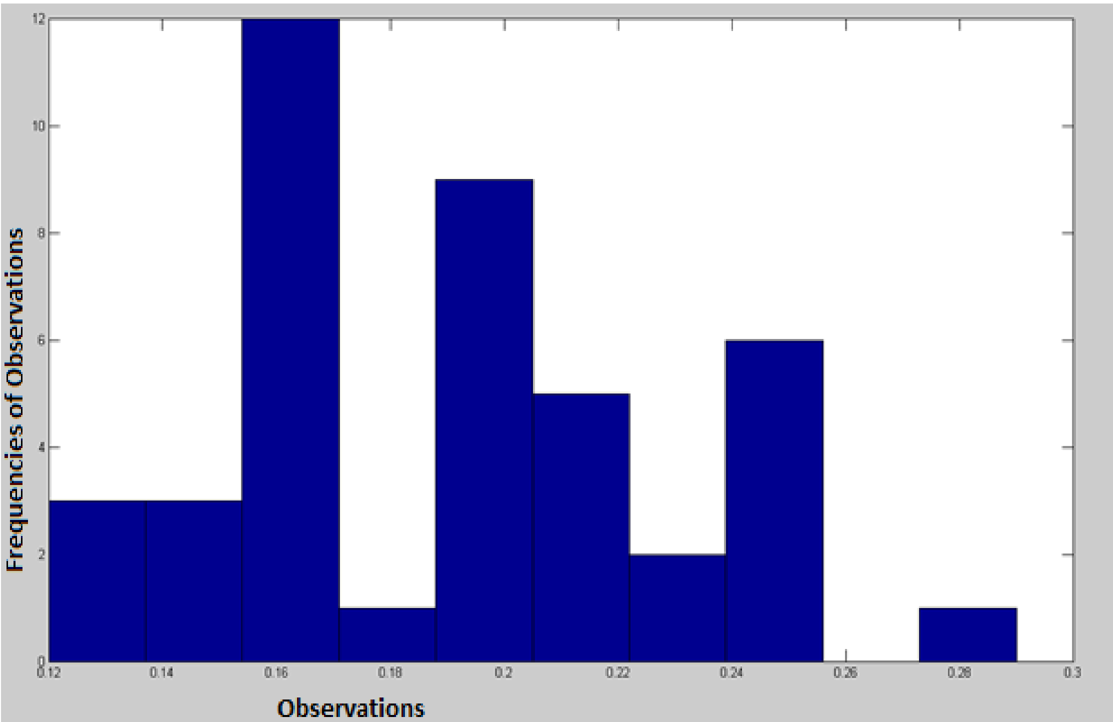

Fig 5.Histogram for Powder Factor(PF)

This continuous or categorical conditions of the independent variables is satisfied by statistical analysis of the variables. Hence it is found that some parameters have only two alternate values throughout the observations which satisfy the ordinal part and other variables are continuous.

The independence of the observations can easily checked using the Durbin-Watson statistic, which is a simple test to run using SPSS.

Table 1:- Durbin Watson statistics of all three dependent variables

	Predictors: (Constant), Penetration Rate	Predictors: (Constant),Bench Height	Predictors: (Constant), Burden	Predictors: (Constant), Spacing	Predictors: (Constant), Stemming	Predictors: (Constant),Blast Round	Predictors: (Constant), L/W
Throw	1.752	1.533	1.597	1.754	1.928	1.507	1.563
Drop	1.906	1.743	1.863	1.683	2.005	1.798	1.837
Powder factor	1.469	1.313	1.574	1.754	1.655	1.217	1.180

Since, all the Durbin-Watson values of the independent variables/parameters are close to 2.Hence it is concluded that this assumption is satisfied by all the variables.

Here this assumption of linear relationship between the dependent variable an each independent variables and the dependent variable and the independent variables collectively is satisfied which is verified using SPSS
Linearity refers to the consistent slope of change that represents the relationship between an IV and a DV. If the relationship between the IV and the DV is radically inconsistent, then it will throw off your SEM analyses. There are dozens of ways to test for linearity. Perhaps the most elegant (easy and clear-cut, yet rigorous), is the deviation from linearity test available in the ANOVA test in SPSS. Then in the ANOVA table in the output window, if the Sig value for Deviation from Linearity is less than 0.05, the relationship between IV and DV is not linear, and thus is problematic (see the screenshots below). Issues of linearity can sometime be fixed by removing outliers (if the significance is borderline), or through transforming the data. If the value of the significance no.is not less than 0.5 then ,linear relationship appear between the variables.

Table 2- DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND BENCH HEIGHT.				
			F	Sig.
Throw * Bench height	Between Groups	(Combined)	1.032	.389
		Linearity	.044	.835
		Deviation from Linearity	1.526	.230
	Within Groups			
	Total			
Drop * Bench height	Between Groups	(Combined)	1.229	.312
		Linearity	1.354	.252
		Deviation from Linearity	1.167	.322
	Within Groups			
	Total			
PF * Bench height	Between Groups	(Combined)	2.694	.060
		Linearity	2.827	.101
		Deviation from Linearity	2.628	.085
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well.

Table 3- DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND BURDEN				
			F	Sig.
Throw * Burden	Between Groups	(Combined)	2.041	.144
		Linearity	2.234	.143
		Deviation from Linearity	1.847	.182
	Within Groups			
	Total			
Drop * Burden	Between Groups	(Combined)	1.047	.361
		Linearity	1.744	.194
		Deviation from Linearity	.350	.558
	Within Groups			
	Total			
PF * Burden	Between Groups	(Combined)	8.430	.001
		Linearity	10.761	.002
		Deviation from Linearity	6.100	.018
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well.

Table 4 DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND SPACING				
			F	Sig.
Throw * Stemming	Between Groups	(Combined)	2.777	.026
		Linearity	7.794	.008
		Deviation from Linearity	1.773	.144
	Within Groups			
	Total			
Drop * Stemming	Between Groups	(Combined)	.750	.613
		Linearity	2.774	.105
		Deviation from Linearity	.346	.882
	Within Groups			
	Total			
PF * Stemming	Between Groups	(Combined)	7.432	.000
		Linearity	39.092	.000
		Deviation from Linearity	1.099	.378
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well.

Table 5- DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND STEMMING				
			F	Sig.
Throw * Stemming	Between Groups	(Combined)	2.462	.062
		Linearity	7.859	.008
		Deviation from Linearity	.663	.580
	Within Groups			
	Total			
Drop * Stemming	Between Groups	(Combined)	1.090	.376
		Linearity	3.150	.084
		Deviation from Linearity	.403	.751
	Within Groups			
	Total			
PF * Stemming	Between Groups	(Combined)	6.252	.001
		Linearity	21.015	.000
		Deviation from Linearity	1.330	.279
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well

Table 6- DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND BLAST ROUND				
			F	Sig.
Throw * Blast round	Between Groups	(Combined)	.308	.921
		Linearity	.417	.635
		Deviation from Linearity	.305	.922
	Within Groups			
	Total			
Drop * Blast round	Between Groups	(Combined)	.288	.930
		Linearity	.257	.701
		Deviation from Linearity	.289	.930
	Within Groups			
	Total			
PF * Blast round	Between Groups	(Combined)	1.918	.525
		Linearity	.002	.970
		Deviation from Linearity	1.968	.520
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well.

Table 7- DEVIATION FROM LINEARITY BETWEEN THROW,DROP,PF AND L/W				
			F	Sig.
Throw * L/W	Between Groups	(Combined)	1.040	.560
		Linearity	.004	.954
		Deviation from Linearity	1.069	.546
	Within Groups			
	Total			
Drop * L/W	Between Groups	(Combined)	.643	.794
		Linearity	.001	.973
		Deviation from Linearity	.661	.781
	Within Groups			
	Total			
PF * L/W	Between Groups	(Combined)	1.185	.494
		Linearity	.569	.492
		Deviation from Linearity	1.202	.486
	Within Groups			
	Total			

Here also the Deviation from linearity values does exceed 0.05 hence these variables satisfies the assumption as well.

This can be concluded considering the values of the above assumptions does obtain significance values above 0.05 so this assumption is met.

The fit line drawn using the variables are drawn and if the line is straight then this assumption that data needs to show homoscedasticity, where the variances along the line of best fit remain similar on moving along the line is satisfied. A simple way to determine if a relationship is homoscedastic, is to do a simple scatter plot with the variable on the x-axis and the variable's residual on the y-axis. If the plot comes up with a consistent pattern - as in the figures then we are good - we have homoscedasticity.

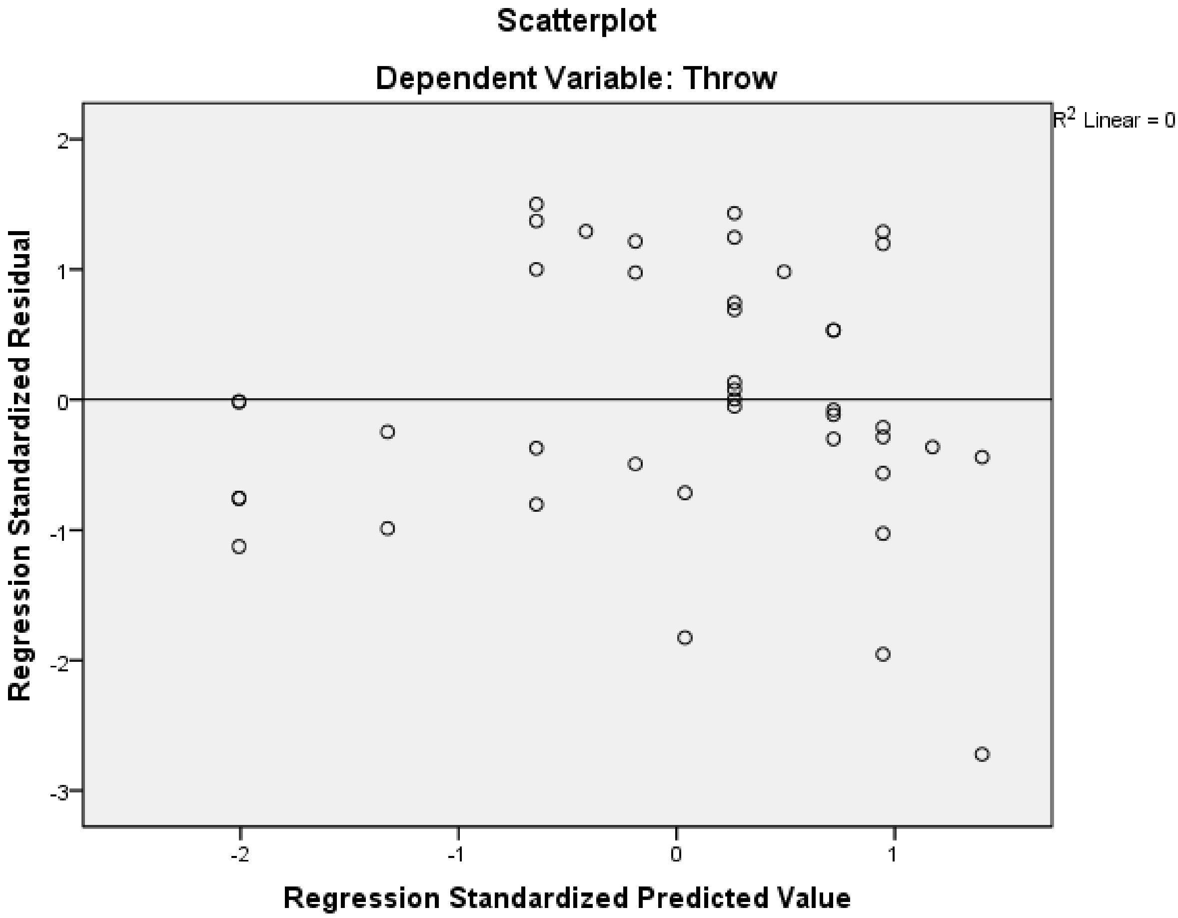

Fig 6: Scatterplot for throw and Drill penetration

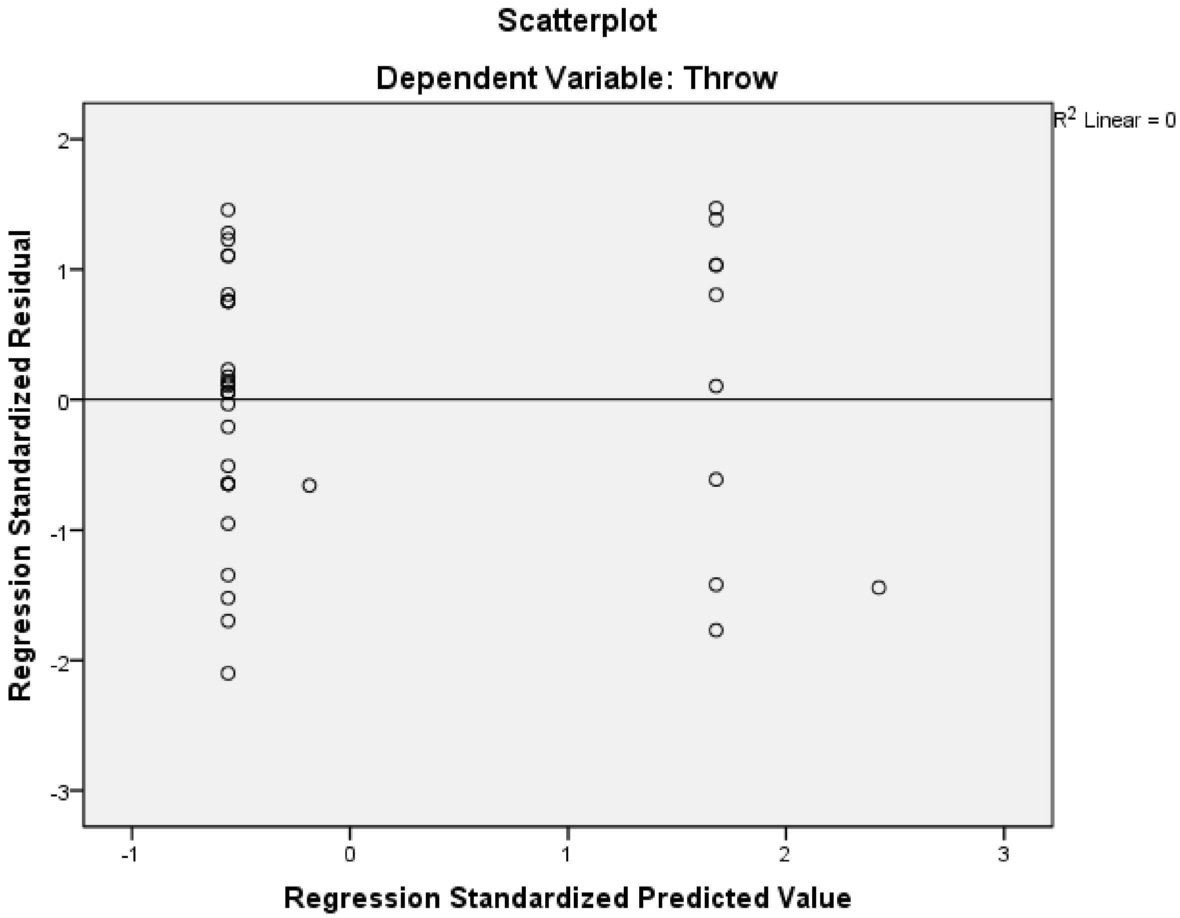

Fig 7:Scatterplot for throw and Bench height

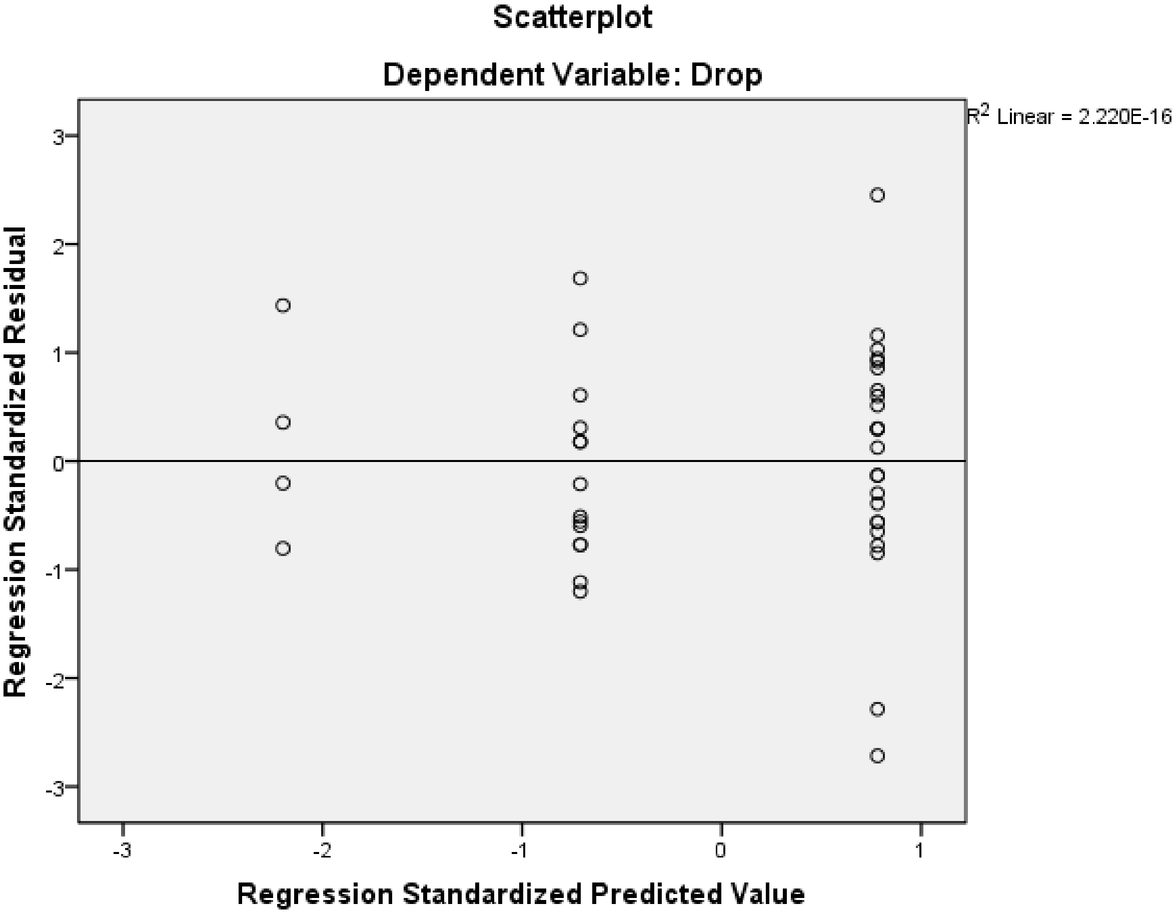

Fig 8:Scatterplot for Burden and Drop

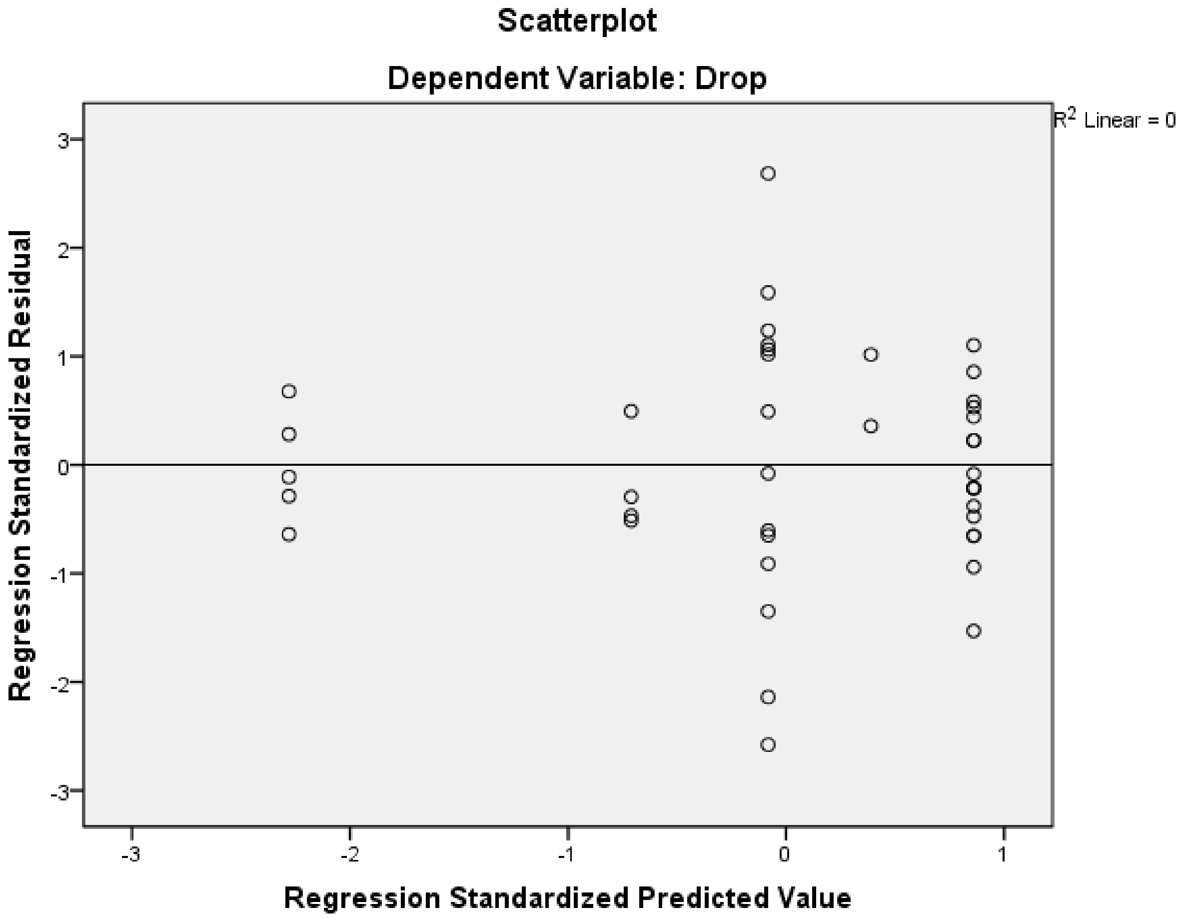

Fig 9:Scatterplot for Stemming and Drop

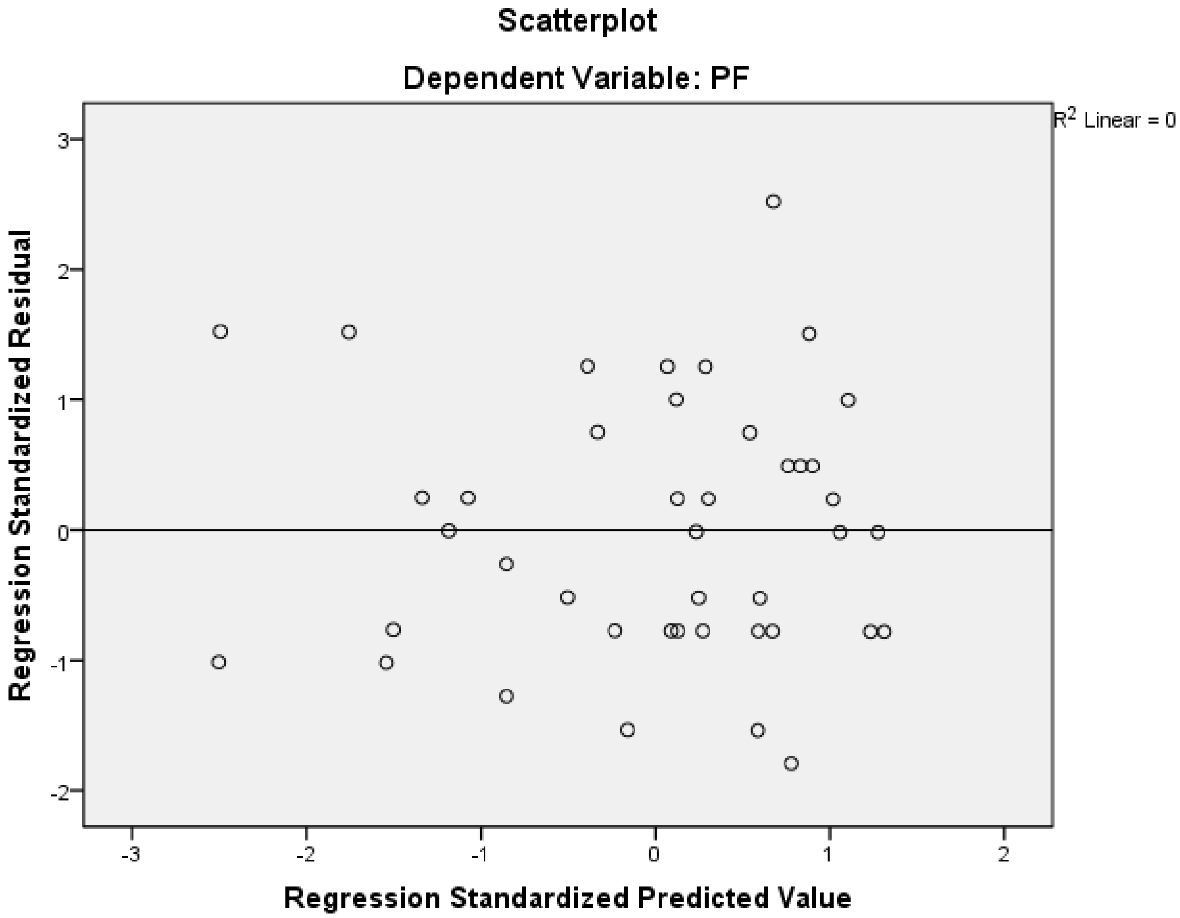

Fig 10:Scatterplot for Blast round and PF

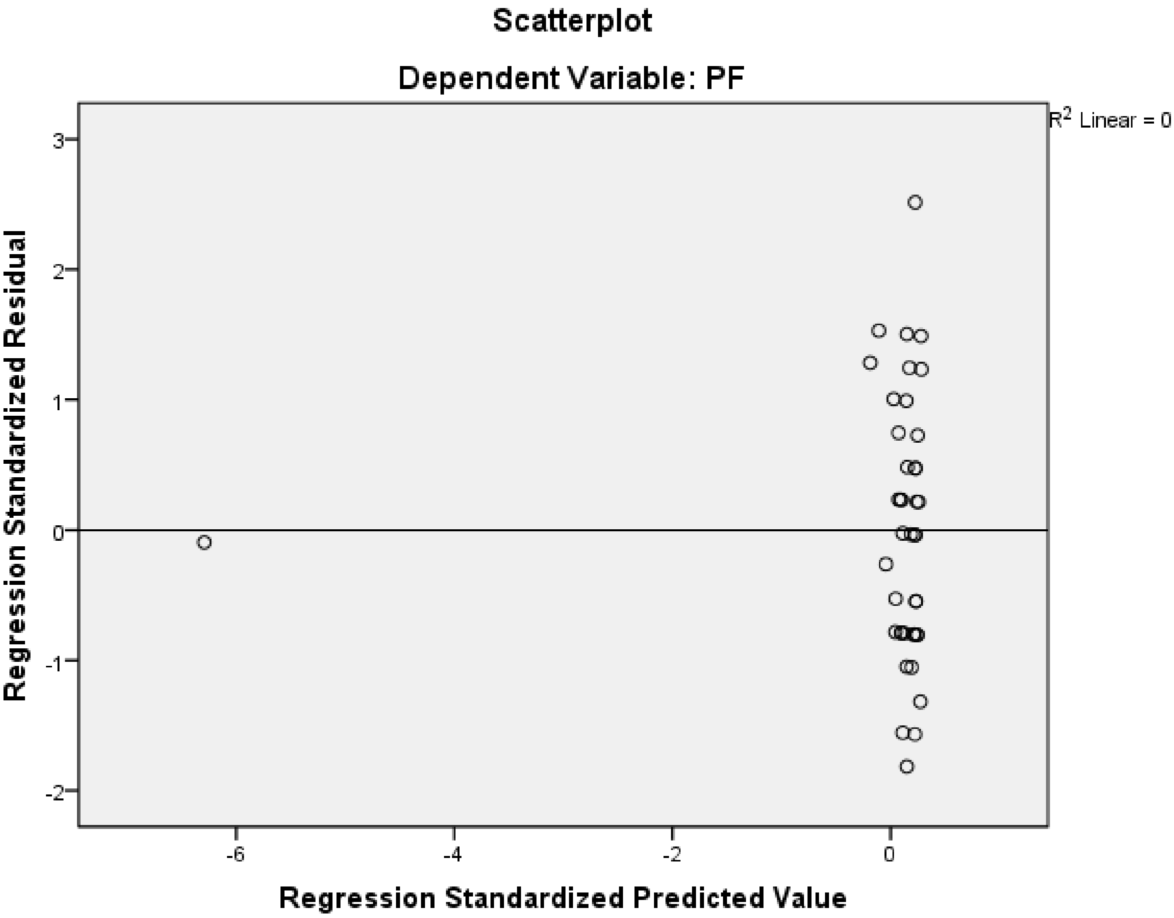

Fig 11:Scatterplot for L/W and PF

Since all the Fit lines of the scatterplots Figures 6-11 are straight lines it is concluded that the data shows homoscedasticity. The other scatterplots and there corresponding fit-lines are not shown due space constraints.

Multicollinearity is not desirable. It means that our independent variables are too highly correlated with each other. The way to check this is to calculate a Variable Inflation Factor (VIF) for each independent variable after running a multivariate regression using one of the IVs (independent Variables) as the dependent variable, and then regressing it on all the remaining IVs. Then swap out the IVs one at a time. If VIF < 3: not a problem with multicollinearity, if VIF > 3; potential problem, if VIF > 5; very likely problem, if VIF > 10; definitely problem

Table 8-Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
	Bench height	.273	3.665
	Burden	.526	1.901
	Spacing	.205	4.875
	Stemming	.346	2.887
	Blast Round	.862	1.160
	L/W	.835	1.197
	PF	.427	2.345

In the above observations The VIF value of Spacing is near to 5 and the value for Bench height is more than 3.

Table 9- Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
	Burden	.520	1.922
	Spacing	.205	4.873
	Stemming	.309	3.238
	Blast Round	.884	1.131
	L/W	.833	1.200
	PF	.425	2.353
	Drill rate	.532	1.879

In the above observations The VIF value of Spacing is near to 5 and the value for Stemming is more than 3.

Table 10- Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
	Stemming	.299	3.345
	Blast Round	.844	1.185
	L/W	.833	1.200
	PF	.423	2.363
	Drill rate	.532	1.879
	Bench height	.273	3.667
	Burden	.508	1.970
	Spacing	.203	4.935

In the above observations The VIF value of Spacing is near to 5 and the value for Stemming and bench height is more than 3.

Under this assumption an independent variable having VIF value near to 5 is eliminated as this value doesn't satisfy the assumption and the variable is Spacing

So ,it is concluded by considering above assumptions that 1 independent variable doesn't meet the requirements and hence are eliminated. The eliminated variable is Spacing.

5.2Forward theory:-

This can be achieved through linear regression approach. In statistics, linear regression is an approach to modeling the relationship between a scalar dependent variable y and one or more explanatory variables denoted X. The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, it is called multiple linear regression and this is distinguished from the multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable. The blasting parameters are used all at a time, knowing the optimum value of such a parameter using the R^2 value so generated by the SPSS software, the maximum R^2 valued parameter is kept constant and the next parameter is inserted into the system. This cycle is continued till all the parameters are optimized. This results in obtaining the proper optimization of all the blasting parameters. Thus a Regression modelling equation is developed.

Table 11:- Model for Throw

			MODEL 1			
	MODEL ❶	MODEL❷	MODEL❸	MODEL❹	MODEL❺	MODEL❻
Drill Penetration			-0.78	-0.084	0.124	-0.073
Bench Height				0.558	0.566	0.562
Burden		-2.104	-2.357	-3.023	-3.156	-3.24
Stemming	-3.629	-3.327	-2.586	-3.412	-3.292	-3.337
Blast Round					-4.00E-04	-4.52E-04
L/W						-0.005
R^2	0.168	0.177	0.185	0.242	0.25	0.252

This table shows how step by step each independent variable is selected keeping the dependent variable (throw) constant. This shows the coefficients of various variables and the corresponding R^2 values. The maximum coefficient throughout the table is of Bench Height ie 0.562 and the R^2 value for this Model is 0.252.

Table 12:-Model for Drop

			MODEL2			
	MODEL❶	MODEL❷	MODEL❸	MODEL❹	MODEL❺	MODEL❻
Drill Penetration					0.034	0.35
Bench Height		0.312	0.331	0.335	0.333	0.331
Burden			-1.491	-1.57	-1.466	-1.496
Stemming	-1.016	-1.562	-1.381	-1.283	-1.589	-1.605
Blast Round				-0.00022	-2.38E-04	-2.42E-04
L/W						-0.002
R^2	0.076	0.181	0.207	0.218	0.226	0.228

The above table shows the selection of variables keeping Drop constant. The step by step selection of different variables is shown. here also Bench Height has the maximum coefficient of 0.331 and the R^2 value is 0.228.

Table 13:-Model for Powder Factor

				MODEL3		
	MODEL❶	MODEL❷	MODEL❸	MODEL❹	MODEL❺	MODEL❻
Drill Penetration				-0.001	-0.001	-0.001
Bench Height						0.001
Burden		-0.079	-0.085	-0.089	-0.086	-0.087
Stemming	-0.071	-0.06	-0.062	-0.051	-0.054	-0.055
Blast Round					8.49E-06	8.45E-06
L/W			-3.30E-04	-3.23E-04	-3.12E-04	-3.12E-04
R^2	0.339	0.405	0.448	0.458	0.473	0.473

This table represents the selection of different independent variables keeping PF constant.As the R^2 values of MODEL❻ doesn't change from the previous one ie MODEL❺ so MODEL❻ can be discarded.

What R^2 means in context of linear regression is "the percentage of deviation that can be explained by this relationship." In other words, R^2 tells a concrete number of how likely it is that can predict the outcomes of whatever it is being studied according to the plot generated. The optimum multi – variate regression equation comes out to be:

Throw = 24.633 - 0.073PR +0.562H – 3.240B – 3.337T -0.000452Q – 0.005L/W (Eqn 10)

Drop = 6.966+0.035PR+0.331H-1.496B-1.605T-0.000212Q-0.002L/W (Eqn 11)

PF = 0.577-0.001PR+0.001H-0.087B-0.055T+0.0000084Q-0.000312L/W (Eqn 12)

Here, PR implies penetration Rate, H implies Bench Height, B implies Burden, T implies Stemming, Q refers to Blast Round, L/W implies Length To Width Ratio

Where 24.6333, 6.966, 0.577 are the constants obtained during linear regression methods of throw, drop and PF respectively. The scatter plots of actual and estimated values of throw, drop, and powder factors are presented in Figure 12, 13, and 14 respectively.

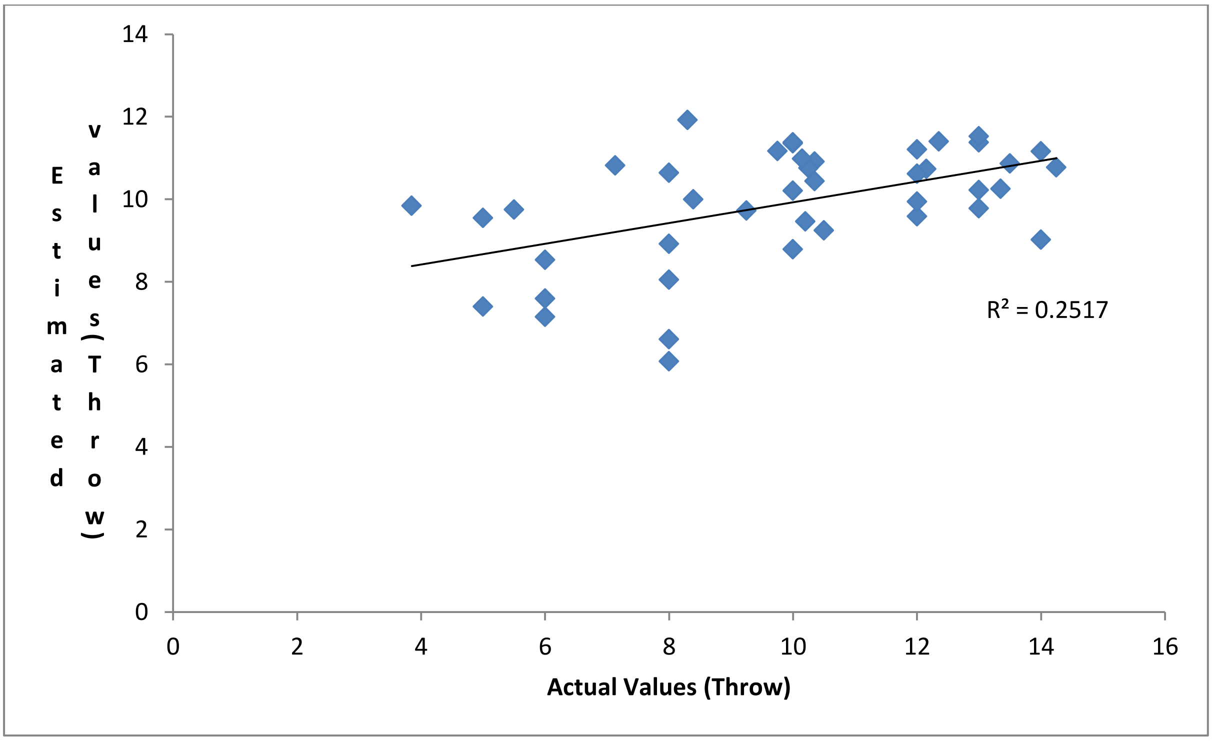

Fig 12:Scatterplots of actual values of throw and estimated values

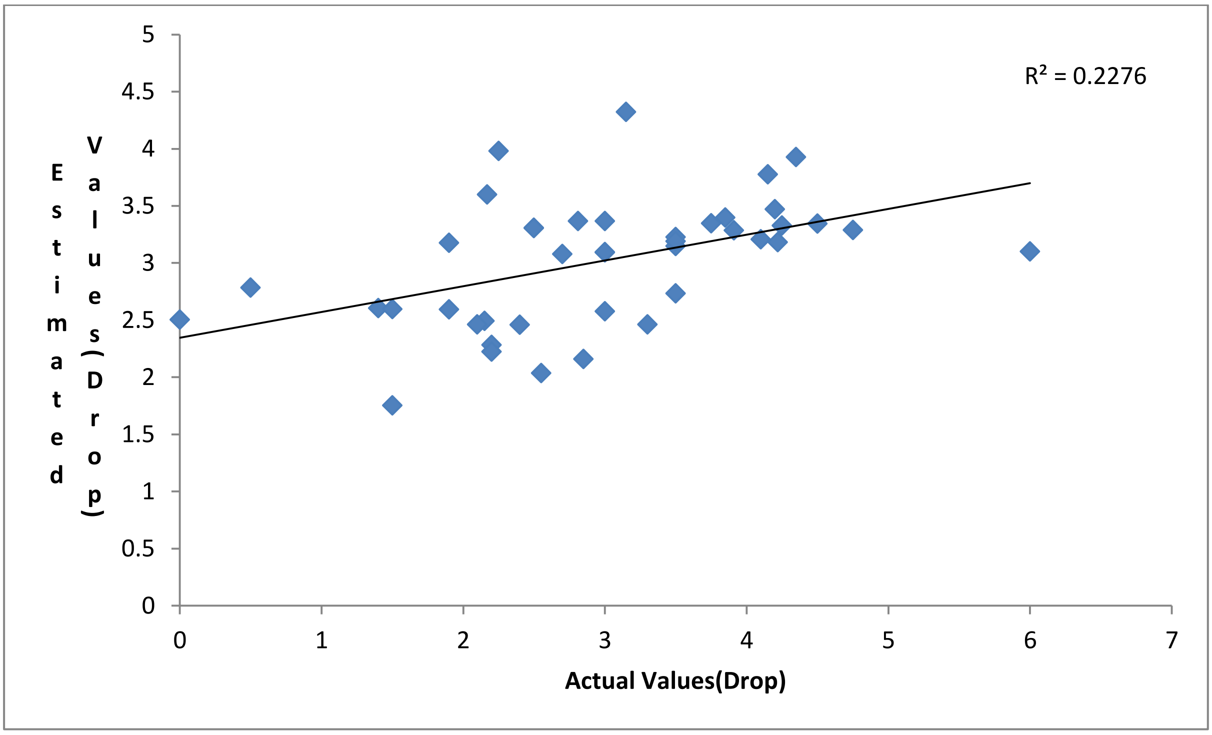

Fig 13: Scatterplots of actual values of drop and estimated values

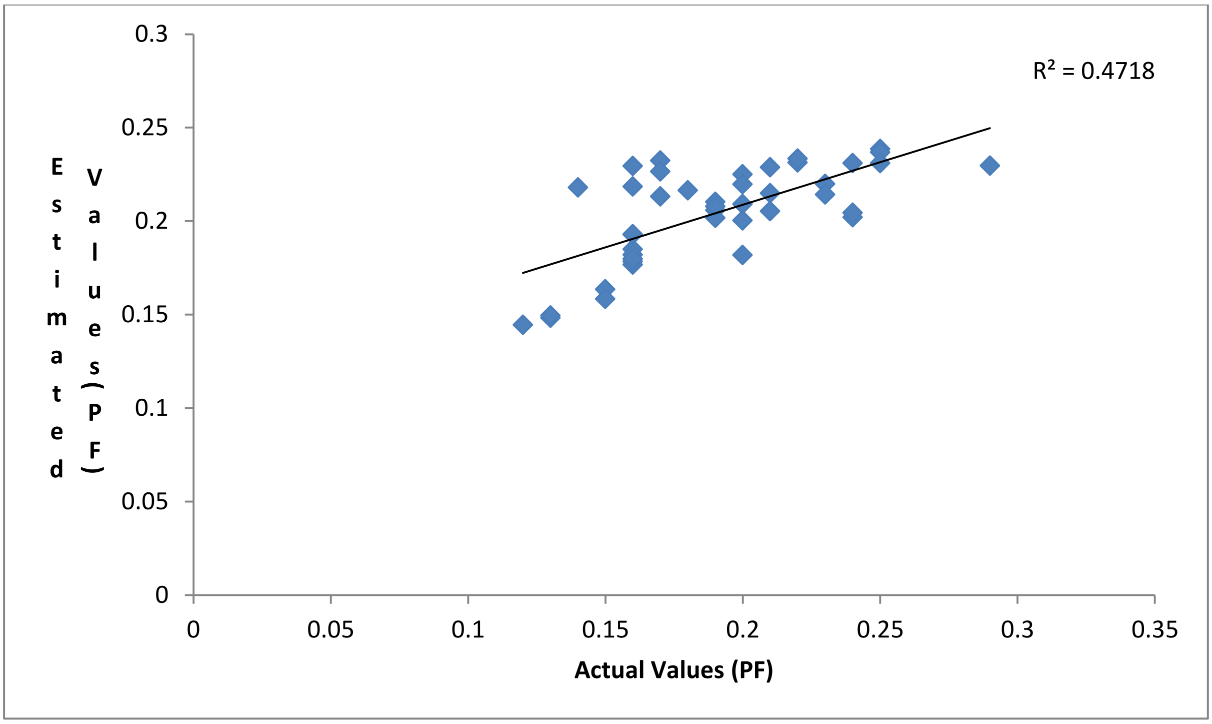

Fig14: Scatterplots of actual values of PF and estimated values

In all the three scatterplots it is evident that the R^2 values are very close to the values obtained by regression model analysis which implies that the estimated values don't differ much from the given actual values.

Error Analysis of the developed models are performed and presented in Table 16.Low mean, and mean absolute errors reveal that the models are nearly unbiased. The variance and mean squared errors are very similar to each other demonstrated that the most of the linear variability of the relations are captured by these developed models.

Table 14:- Error model for throw, drop and powder factor

	MODEL throw	MODEL drop	MODEL powder factor
Mean	-0.00457	-0.04952	-0.01401
Variance	5.954577	1.061424	0.000802
Mean square Error	5.81	1.038	9.79e-4
Absolute mean error	0.00457	0.04952	0.01401

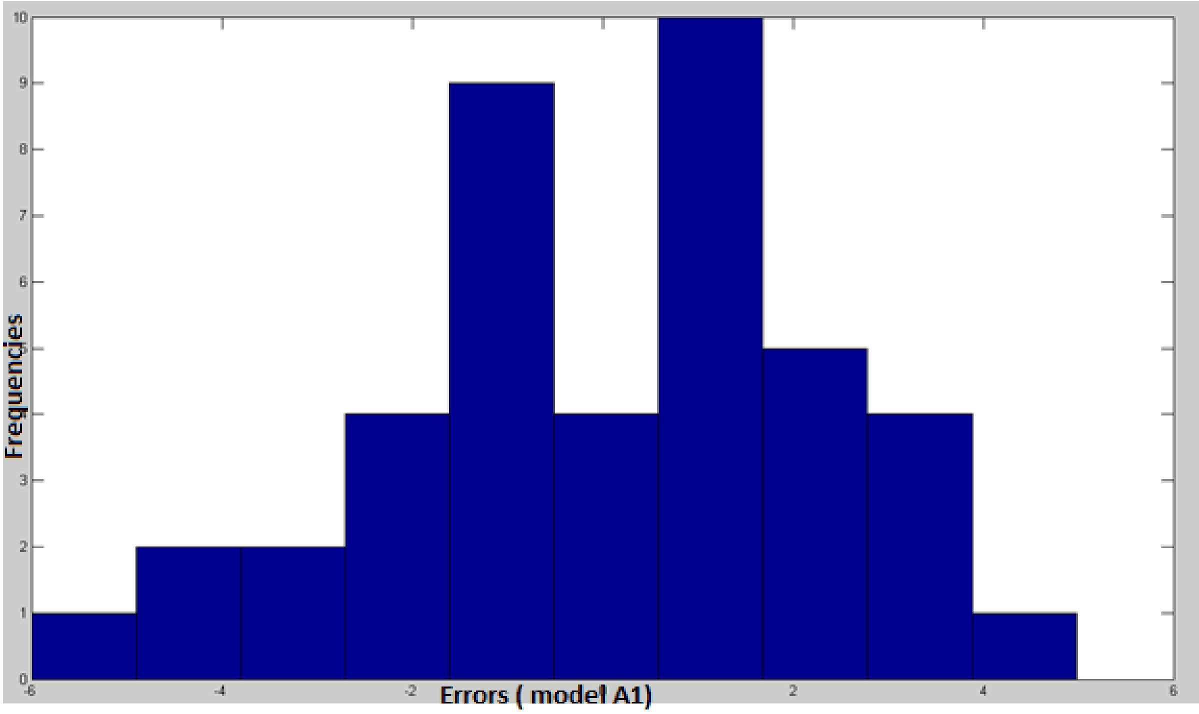

Fig 15: Histogram for the Errors in the values of Throw

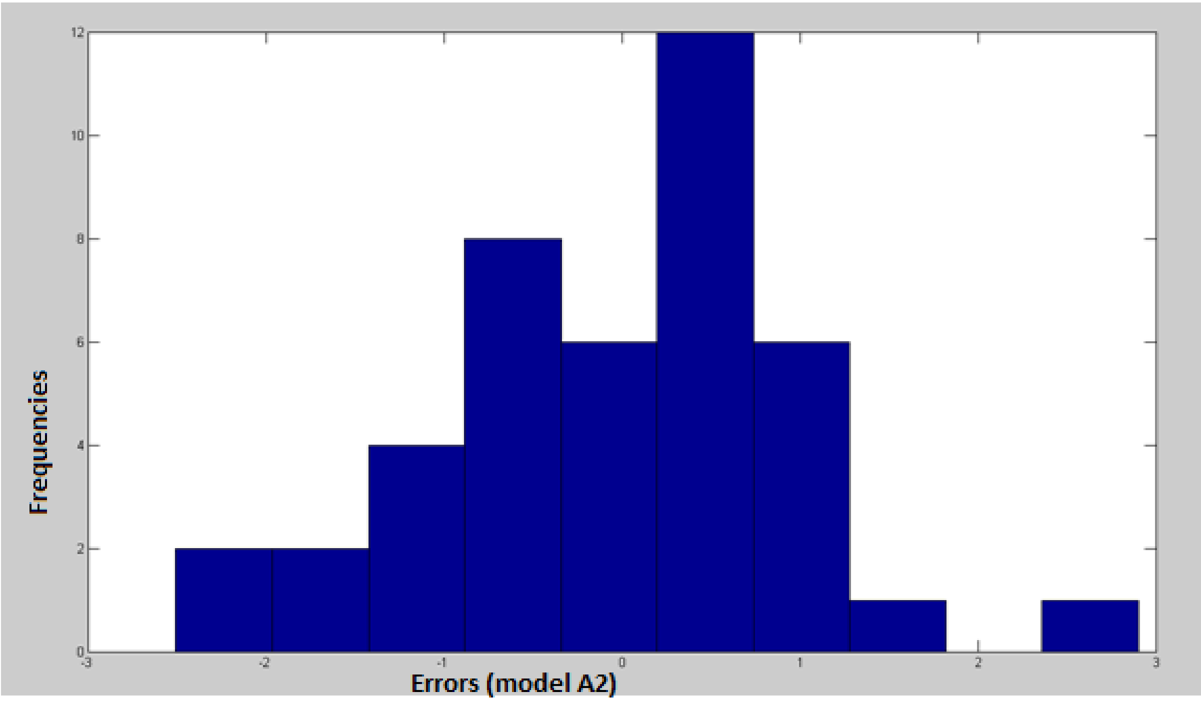

Fig 16: Histogram for the Errors in the values of Drop

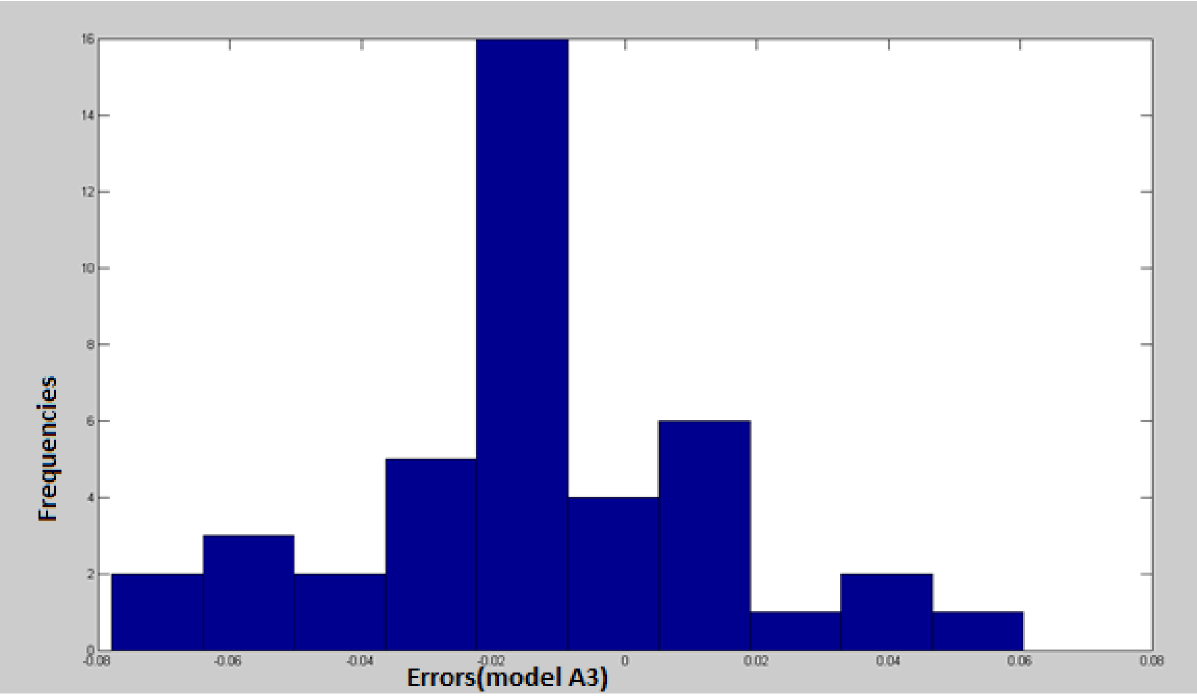

Fig 17:Histogram for the errors in the values of PF

The above Histograms show that the errors of the models are normally distributed and follow Gaussian distribution with zero mean.

The paired samples t-test was performed to see whether the estimated means are matching with the actual means of the dependent variables.

Table 15:-Paired sample t test for throw

	Paired Differences				
				95% Confidence Interval of the Difference	
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper
Pair 1 Ethrow – Throw	.0045674	2.4402002	.3765311	-.7558525	.7649873

	t	df	Sig. (2-tailed)
Pair 1 Ethrow – Throw	.012	41	.990

Ethrow refers to the Estimated throw, the column labelled ”Mean” is the difference of the two means(the difference is due to round off error).The next column is the standard deviation of the difference between the two variables.

The column labeled "t" gives the observed or calculated t value. (you can ignore the sign.) The column labeled "df" gives the degrees of freedom associated with the t test. The column labeled "Sig. (2-tailed)" gives the two-tailed p value associated with the test. In this, the p value is .990. If this had been a one-tailed test, we would need to look up the critical value of t in a table.

Table 16:-Paired sample t test for drop

		Paired Differences				
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference	
					Lower	Upper
Pair 1	Edrop - Drop	.0495162	1.0302545	.1589717	-.2715337	.3705661

		t	df	Sig. (2-tailed)
Pair 1	Edrop - Drop	.311	41	.757

The column labeled "Sig. (2-tailed)" gives the two-tailed p value associated with the test. In this , the p value is .757. If this had been a one-tailed test, we would need to look up the critical value of t in a table.

Table 17:-Paired sample t test for powder factor

	Paired Differences				
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference	
				Lower	Upper
Pair 1 EPf - PF	.0140089	.0283198	.0043698	.0051839	.0228340

	t	df	Sig.(2tailed)
Pair 1 EPf - PF	3.206	41	.003

Results revealed that the estimated means are not significant different for drop and throw; however, t-test of powder factor revealed that the means are different.

5.3 Inverse Theory:-

Here the inverse of the matrix obtained is calculated by pseudo-inverse which can be expressed from the singular value decomposition (SVD) of B.Now calculating the above derived equation we get a matrix let's say

C= [-5.5818 105682 27.2669

-2.6035 5.6321 -1.4636

1.0970 -1.3188 -29.2358

-1.6811 1.9963 27.5435

-0.0042 0.0070 0.0431

$$0.0178 \quad -0.0024 \quad -0.3492]$$

So, C(Y)=X

$$\begin{pmatrix} -5.5818 & 10.5682 & 27.2669 \\ -2.6035 & 5.6321 & -1.4636 \\ 1.0970 & -1.3188 & -29.2358 \\ -1.6811 & 1.9963 & 27.5435 \\ -0.0042 & 0.0070 & 0.0431 \\ 0.0178 & -0.0024 & -0.3492 \end{pmatrix} \begin{pmatrix} Y_1-C_1 \\ Y_2-C_2 \\ Y_3-C_3 \end{pmatrix} = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \end{pmatrix}$$

The inverse theory equations of all 7 independent variables are presented here:

$$-5.5818(Y_1-C_1)+10.5682(Y_2-C_2)+27.2669(Y_3-C_3) = X_1$$

$$-2.6035(Y_1-C_1)+5.6321(Y_2-C_2)-1.4636(Y_3-C_3) = X_2$$

$$1.0970(Y_1-C_1)-1.3188(Y_2-C_2)-29.2358(Y_3-C_3) = X_3$$

$$-1.6811(Y_1-C_1)+1.9963(Y_2-C_2)+27.5435(Y_3-C_3) = X_4$$

$$-0.0042(Y_1-C_1)+0.0070(Y_2-C_2)+0.0431(Y_3-C_3) = X_5$$

$$0.0178(Y_1-C_1)-0.0024(Y_2-C_2)-0.3492(Y_3-C_3) = X_6$$

C_1, C_2, C_3 are the constants mentioned earlier. Y_1, Y_2, Y_3 are the different observations for the three dependent variables which gives the corresponding outputs of the independent variables. Table 20 presents the error statistics of linear inverse model developed in this thesis. The results demonstrated that inverse model under-estimate the variables penetration rate, bench height, stemming; whereas, over-estimate burder, blast round and L/ W ratio.

Table 18:-Error statistics of linear inverse model

	Penetration Rate	Bench Height	Burden	Stemming	Blast Round	L/W
Mean	-2.35416	-12.8652	4.798939	-7.44915	733.4757	6.625671
Variance	28.91971	0.118477	1.071838	3.608878	109045.1	0.643613
R^2	0.1207	0.0401	0.003	0.0469	0.0151	0.003

CHAPTER 6

CONCLUSION

6. CONCLUSION:-

A study was carried out to solve the blasting proceeses using inverse theories. From the equation, it is clearly seen that the change in the value of Hole Depth , Blast round and Spacing have no effect on the Throw,Drop and Powder Factor for such mine.Bench Height has highest impact on the three dependent variables.L/W and drill penetration Rate has the next highest impact on Throw,Drop and bench height respectively.Some estimated values of the independent variables vary largely from the original or actual values according to the inverse theory, from this theory it can be inferred that the penetration rate affects the most among the other variables to Throw,Drop and Powder Factor,the next most effective variables are Burden,L/W,Stemming,Bench height and Blast round respectively. The results demonstrated that inverse model under-estimate the variables penetration rate, bench height, stemming; whereas, over-estimate burder, blast round and L/ W ratio.

CHAPTER 7

REFERENCES

7. **REFERENCES**

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